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Research on Dynamic Blur Restoration Technology for Low-Altitude Flight Images

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Abstract: Low-altitude flight images are prone to dynamic blur due to platform disturbances, complex scene motion, and dynamic exposure variations. This degradation significantly limits the performance of subsequent tasks such as target recognition and geographic information extraction. Starting from the dynamic blur characteristics of low-altitude flight images, this paper systematically analyzes scene image features, classification of blur causes, and mathematical modeling foundations. It focuses on constructing a dynamic blur restoration technology framework and discusses key components including image preprocessing, blur feature extraction, core restoration modules, and result optimization and evaluation. Based on the latest advances in deep learning, the research integrates physical priors with data-driven methods to provide a systematic technical approach for dynamic blur restoration in low-altitude flight images, helping to improve the quality of image acquisition and the reliability of low-altitude observation systems.

Keywords: Low-altitude flight image; Dynamic blur restoration; Feature extraction; Deep learning; Image quality assessment

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1. Introduction

With the wide application of low-altitude observation technology in various fields, the quality of low-altitude flight image acquisition determines the accuracy and effectiveness of subsequent data analysis. Affected by factors such as flight platform attitude changes, dynamic target motion, and adjustments of the camera auto-exposure system, low-altitude flight images generally exhibit dynamic blur with degradation features such as edge diffusion and detail loss, which reduce the information-carrying capacity of the images. Dynamic blur restoration technology is crucial for improving image quality, aiming to reverse image degradation and restore clear scene information. Traditional restoration methods are limited by fixed assumption models and struggle to adapt to complex blur scenarios, while deep learning technology provides a new approach. This paper summarizes the dynamic blur characteristics of images, constructs a more adaptable restoration technology framework, focuses on the collaborative design of core technologies, and provides theoretical and technical references for the practical development of the technology.

2. Analysis of dynamic blur characteristics of low-altitude flight images

2.1. Image features of low-altitude flight scenarios

In low-altitude flight scenarios, the imaging environment is complex and dynamic, with core features including uneven richness of scene textures, obvious geometric distortion, multiple noise sources, and variable lighting conditions. Flying close to ground targets results in abundant ground object details, but texture feature differences are large, forming diverse texture distributions. Affected by flight platform attitude and lens optical characteristics, images are prone to geometric distortion, and the degree of distortion changes dynamically with flight attitude. Imaging is affected by multiple noise sources, especially under low-light conditions. In addition, light intensity changes rapidly due to clouds, terrain, etc., leading to uneven image brightness and exacerbating image degradation. These characteristics make the dynamic blur of low-altitude flight images more uncertain and non-uniform, increasing the difficulty of restoration technology implementation [1].

2.2. Causes and classification of dynamic blur

The causes of dynamic blur in low-altitude flight images are multi-factor coupled, mainly attributed to three categories: flight platform motion, scene target motion, and imaging system characteristics. Flight platforms experience attitude changes due to low-altitude airflow disturbances, causing relative motion between the camera and the scene, which is the main cause of dynamic blur. Dynamic targets in the scene move during the imaging exposure time, forming local blur regions. The camera's auto-exposure adjustments cause dynamic changes in exposure time, which couple with motion factors to form complex spatiotemporal degradation patterns. Mismatches between shutter speed and motion speed further exacerbate blur. According to blur characteristics, dynamic blur is classified into space-invariant and space-variant types. Space-invariant blur is mostly caused by uniform translation of the flight platform, with a consistent blur kernel across the entire image. Space-variant blur is caused by platform rotation, vibration, or local dynamic target motion, with blur kernels changing with image position. This type of blur is more common and more difficult to restore.

2.3. Mathematical modeling foundation of blurred images

Mathematical modeling of dynamic blurred images is the theoretical basis for effective restoration, and its core is to construct a mapping relationship from clear images to blurred images. For space-invariant dynamic blur, the classic modeling method uses a convolution model, representing the blurred image as the convolution of the clear image and the blur kernel plus noise interference. That is, it describes the quantitative relationship between the pixel values of the blurred image and the clear image, the blur kernel parameters, and the noise, where the blur kernel characterizes the pixel diffusion pattern caused by motion. For space-variant dynamic blur that is more suitable for low-altitude flight scenarios, a variational convolution model is adopted, introducing a spatially dependent dynamic blur kernel to accurately model the degradation process at different spatial positions. In recent years, physics-based modeling has become a research hotspot, explicitly modeling the coupling effect of motion and exposure, introducing exposure time as a physical quantity into the model design, and constructing a degradation model that is more consistent with the real imaging process. Meanwhile, combining IMU data from the flight platform and camera parameters can further improve the adaptability of the blur model, providing a more reliable theoretical basis for subsequent restoration algorithm design.

3. Design of dynamic blur restoration technology framework

3.1. Image preprocessing and blur feature extraction

Image preprocessing and blur feature extraction are the fundamental prerequisites for dynamic blur restoration, with the core goals of reducing noise interference, correcting geometric distortion, and accurately capturing blur-related features to provide high-quality input data for subsequent restoration algorithms. The preprocessing stage adopts a layered denoising strategy: first, adaptive Gaussian filtering suppresses sensor Gaussian noise, median filtering eliminates saltand-pepper noise, and then an atmospheric transmission model compensates for image attenuation caused by atmospheric turbulence to improve the signal-to-noise ratio. For geometric distortion, lens distortion correction algorithms based on camera internal parameters and flight attitude data correct barrel or pincushion distortion to ensure the accuracy of image geometric information [2]. The blur feature extraction stage leverages deep learning to build a multi-scale feature extraction network, capturing low-frequency structural features and high-frequency detail features of blurred images through the deep structure of convolutional neural networks. Attention mechanisms are introduced to enhance feature perception in blurred edge regions, and optical flow methods are combined to extract motion vector features between adjacent frames to construct a multi-dimensional feature fusion matrix. For dynamic exposure scenarios, an exposure-aware feature module is designed to extract feature information related to exposure time changes, realizing the joint representation of blur features and exposure features and providing comprehensive feature support for subsequent accurate restoration.

3.2. Core modules of restoration algorithms

The core module of the restoration algorithm is the key support of the dynamic blur restoration technology framework. Based on the design concept of fusing data-driven and physical priors, an end-to-end restoration architecture suitable for complex low-altitude blur scenarios is constructed. A task decoupling strategy is adopted, decoupling dynamic blur restoration and detail enhancement into independent branches, and using a dual-branch structure to complete blur kernel estimation and clear image reconstruction respectively. The deblurring branch uses an asymmetric residual encoder-decoder structure to expand the receptive field through multi-scale down-sampling, accurately capture global blur features, and achieve preliminary deblurring. The detail enhancement branch directly extracts high-frequency detail features from blurred images through a dense residual block structure to avoid error accumulation caused by relying on intermediate results.

Furthermore, a dynamic gating fusion module is introduced to generate pixel-level weight maps to adaptively fuse dual-branch features, suppress error propagation, and improve the detail fidelity of restored images. For long-sequence low-altitude flight images, a bidirectional propagation hierarchical refinement module is designed to achieve sequence-level parallel processing, expand the temporal receptive field, and improve processing efficiency, solving the efficiency bottleneck of traditional recurrent networks’ serial processing. In addition, a generative adversarial network mechanism is integrated to build a dual-scale discriminator, optimizing the visual perception quality of restored images through adversarial training between the generator and the discriminator to make the restoration results more in line with human visual characteristics. Physical prior constraints are embedded, converting the mathematical relationships of blur modeling into network regularization terms to improve the algorithm’s adaptability and robustness to complex blur scenarios.

3.3. Optimization and evaluation of restoration results

The improvement and evaluation of restoration results are important steps to ensure the quality of dynamic blur restoration. Various improvement methods are used to enhance the restoration effect, and a scientific and complete evaluation system is established to measure restoration performance. In the improvement stage, post-processing enhancement methods are used. For possible edge blurring and color imbalance in restored images, adaptive sharpening methods enhance edge details, and color adjustment technologies are combined to adjust image color balance and restore real scene colors. A noise suppression post-processing part is added, using wavelet threshold denoising to remove noise amplified during the restoration process to achieve a balance between detail enhancement and noise suppression.

The evaluation system combines subjective and objective evaluation. Objective evaluation selects two types of metrics, full-reference and no-reference. Full-reference metrics use peak signal-to-noise ratio and multi-scale structural similarity to measure pixel-level differences between restored images and clear images, and use perception-based similarity metrics to evaluate visual perception quality. No-reference metrics use natural image quality evaluation metrics, suitable for real low-altitude flight scenarios without clear reference images. Subjective evaluation uses mean opinion scores to count observers’ subjective views on the clarity and detail integrity of restored images. Comprehensive subjective and objective evaluation results comprehensively judge the performance of the restoration algorithm and provide a reliable basis for algorithm improvement [3].

4. Conclusion

Dynamic blur restoration technology for low-altitude flight images is of great significance for improving low-altitude observation efficiency. By deeply analyzing the image characteristics of low-altitude flight scenarios, the causes and classification of dynamic blur, and the mathematical modeling foundation, a complete technical framework covering image preprocessing, blur feature extraction, core modules of restoration algorithms, and result optimization and evaluation is constructed. This framework integrates the advantages of deep learning and physical priors, taking into account the flexibility of data-driven methods and the reliability of physical law constraints, effectively addressing complex low-altitude blur scenarios. It provides innovative ideas and practical methods for improving the quality of low-altitude flight images and ensuring the reliability of subsequent applications, promoting the development of low-altitude observation technology toward higher quality and wider application.

Disclosure statement

The author declares no conflict of interest.

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